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Szeliski et al.

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(54) **SYSTEM AND METHOD FOR EXTRACTING REFLECTION AND TRANSPARENCY LAYERS FROM MULTIPLE IMAGES**

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G06K 9/00 (2006.01)

(52) **U.S. Cl.** **382/107**; 382/103; 382/173; 382/190

(58) **Field of Classification Search** 382/107, 382/103, 173, 190
See application file for complete search history.

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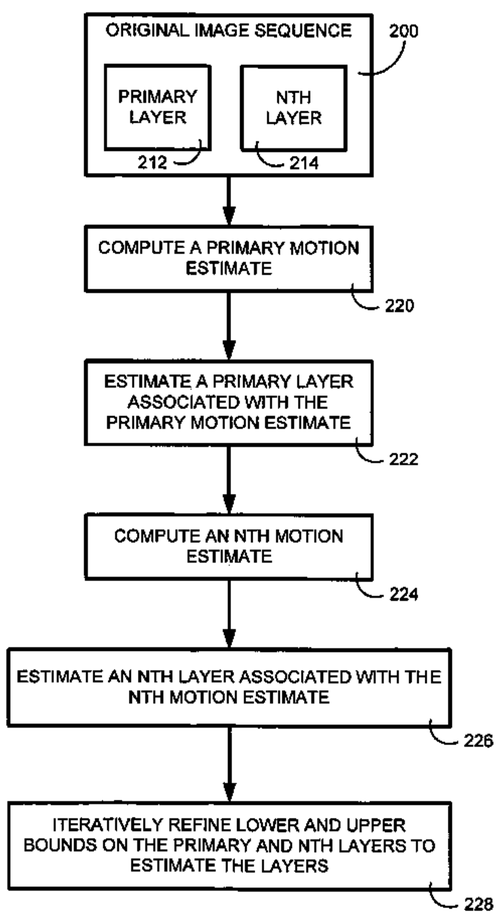
Primary Examiner—Andrew W. Johns
Assistant Examiner—Patrick L. Edwards
(74) *Attorney, Agent, or Firm*—Lyon & Harr, LLP; Katrina A. Lyon

(57) **ABSTRACT**

The present invention is embodied in a system and method for extracting structure from multiple images of a scene by representing the scene as a group of image layers, including reflection and transparency layers. In general, the present invention performs layer extraction from multiple images containing reflections and transparencies. The present invention includes an optimal approach for recovering layer images and their associated motions from an arbitrary number of composite images. The present invention includes image formation equations, the constrained least squares technique used to recover the component images, a novel method to estimate upper and lower bounds on the solution using min- and max-composites, and a motion refinement method.

19 Claims, 9 Drawing Sheets



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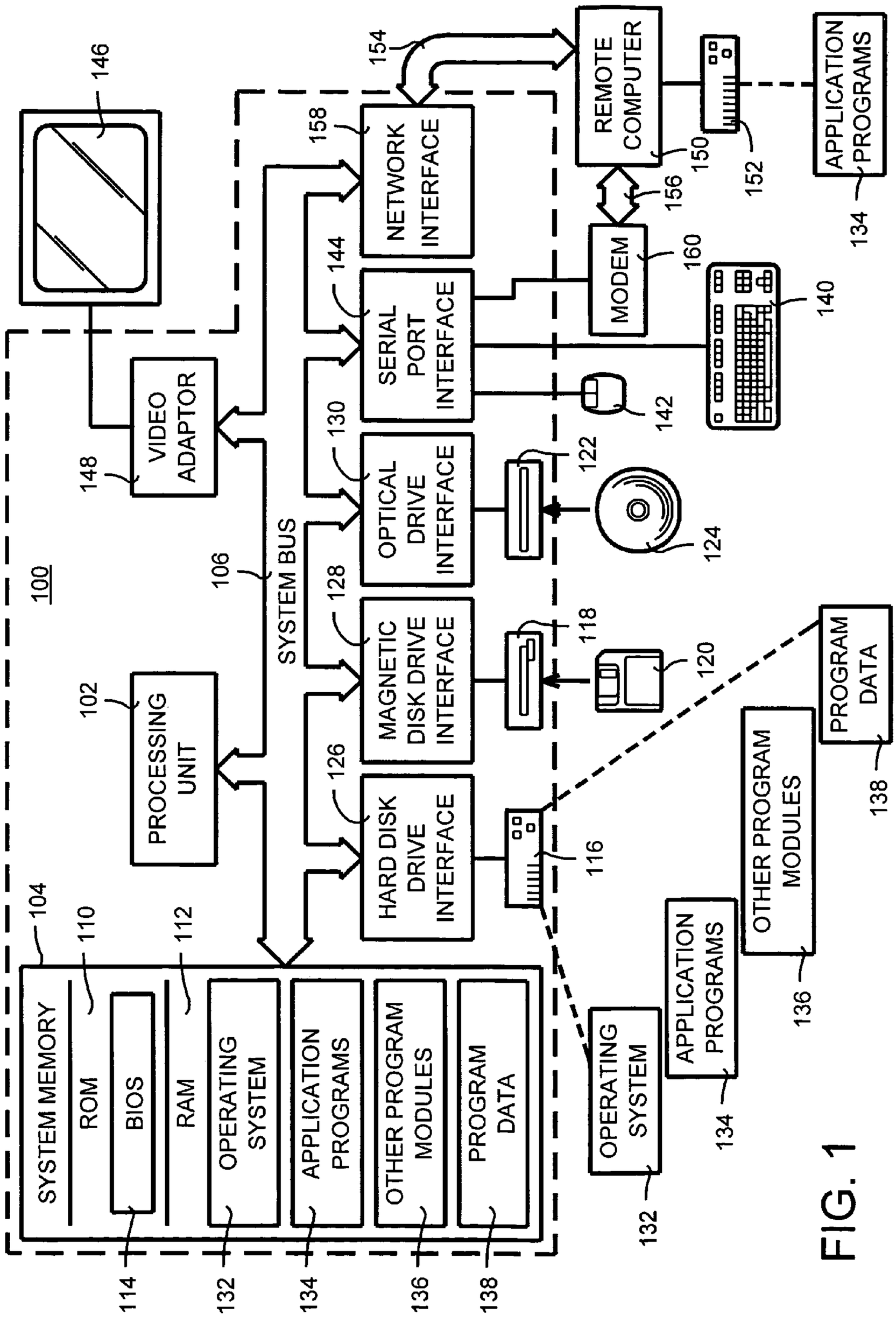
146
154
158
NETWORK INTERFACE
REMOTE COMPUTER
150
152
APPLICATION PROGRAMS
134
156
160
MODEM
144
SERIAL PORT INTERFACE
140
142
130
OPTICAL DRIVE INTERFACE
122
124
148
VIDEO ADAPTOR
100
106
SYSTEM BUS
128
MAGNETIC DISK DRIVE INTERFACE
118
120
102
PROCESSING UNIT
126
HARD DISK DRIVE INTERFACE
116
PROGRAM DATA
138
OTHER PROGRAM MODULES
104
110
112
SYSTEM MEMORY
ROM
BIOS
RAM
OPERATING SYSTEM
APPLICATION PROGRAMS
OTHER PROGRAM MODULES
PROGRAM DATA
OPERATING SYSTEM
APPLICATION PROGRAMS
114
132
134
136
138
132
134
136

FIG. 1

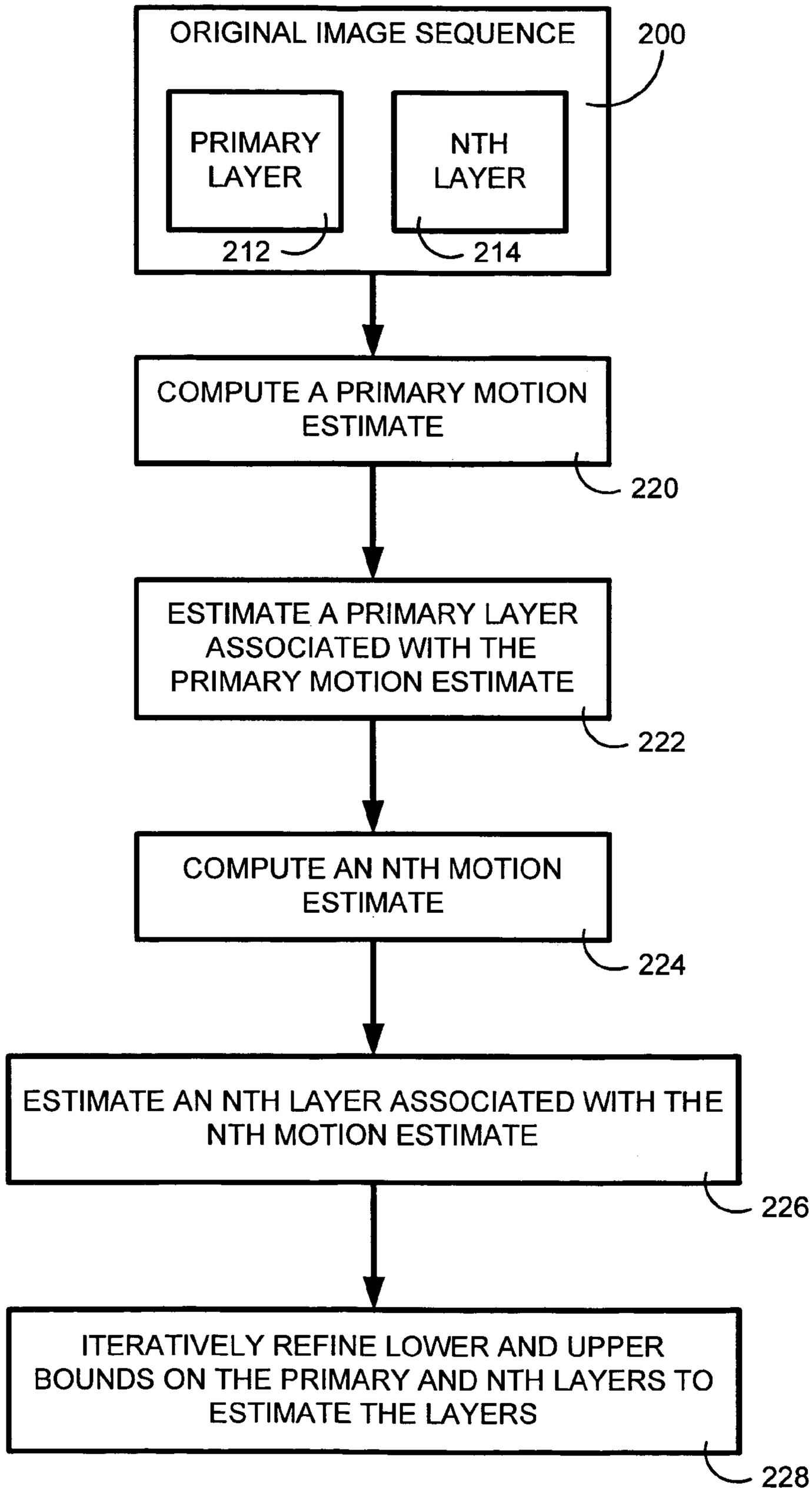
ORIGINAL IMAGE SEQUENCE
200
PRIMARY LAYER
NTH LAYER
212
214
COMPUTE A PRIMARY MOTION ESTIMATE
220
ESTIMATE A PRIMARY LAYER ASSOCIATED WITH THE PRIMARY MOTION ESTIMATE
222
COMPUTE AN NTH MOTION ESTIMATE
224
ESTIMATE AN NTH LAYER ASSOCIATED WITH THE NTH MOTION ESTIMATE
226
ITERATIVELY REFINE LOWER AND UPPER BOUNDS ON THE PRIMARY AND NTH LAYERS TO ESTIMATE THE LAYERS
228

FIG. 2

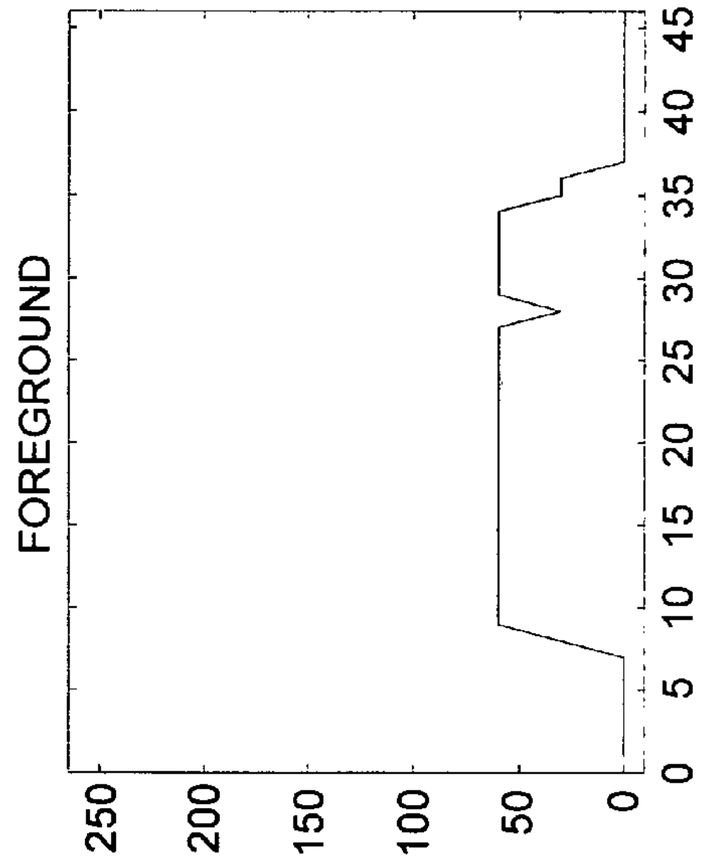

FIG. 3B

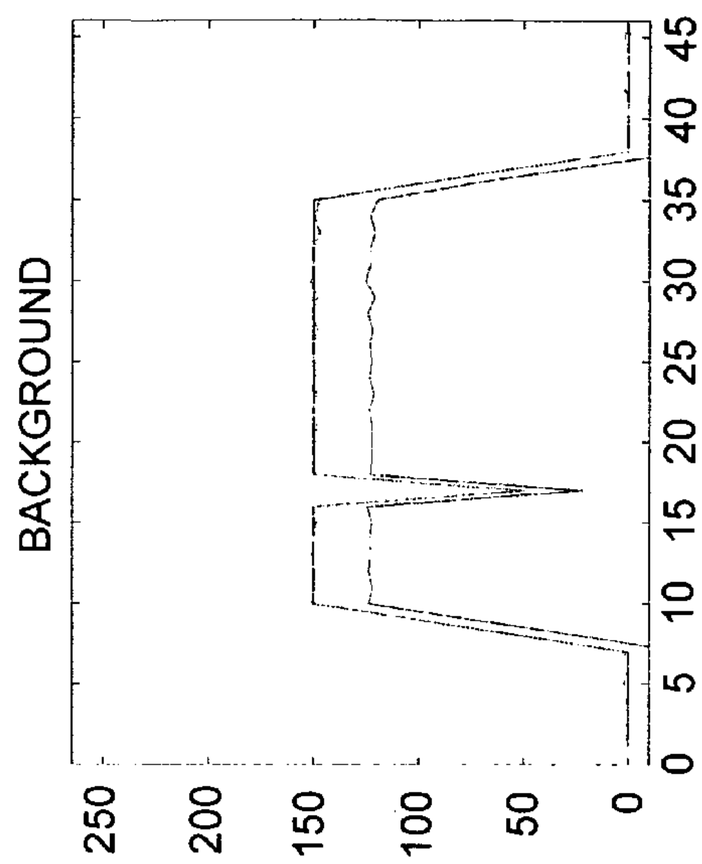

FIG. 3D

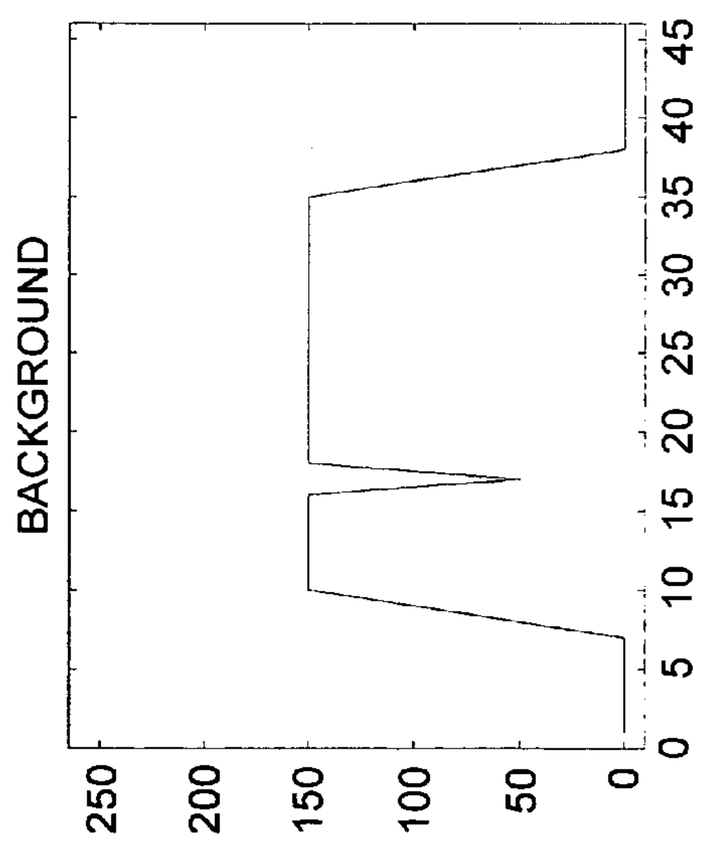

FIG. 3A

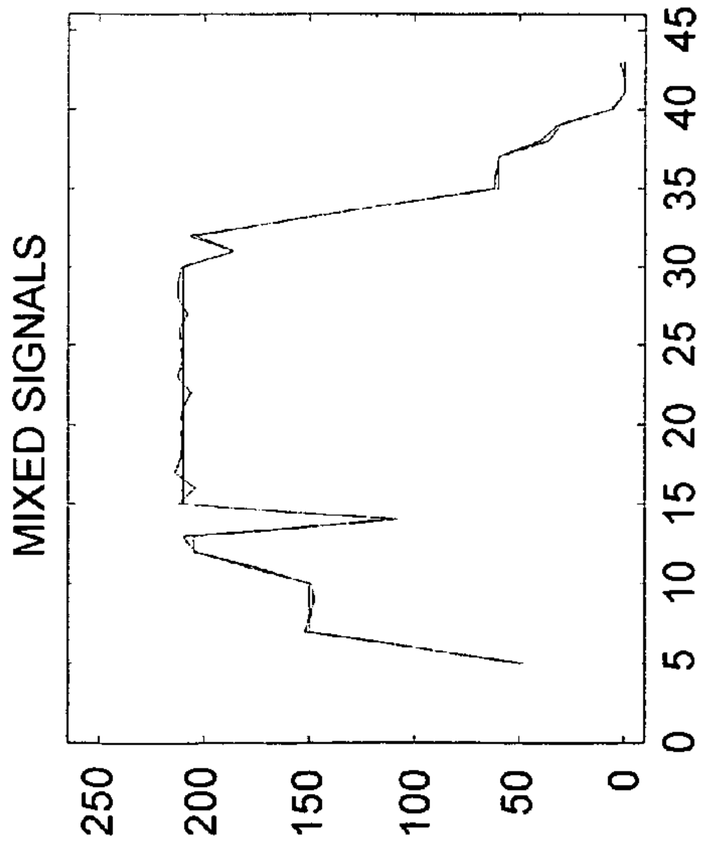

FIG. 3C

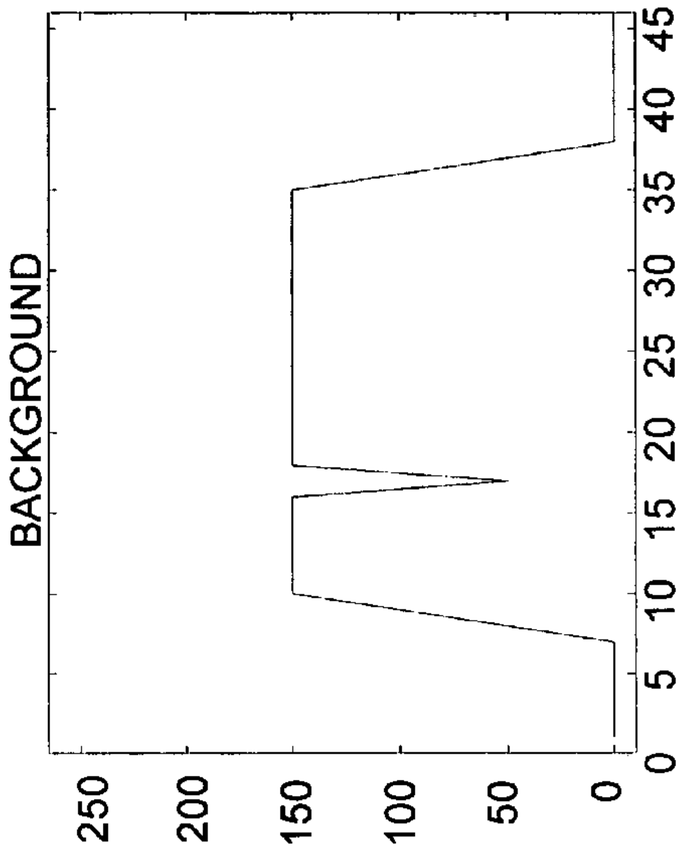

FIG. 4A

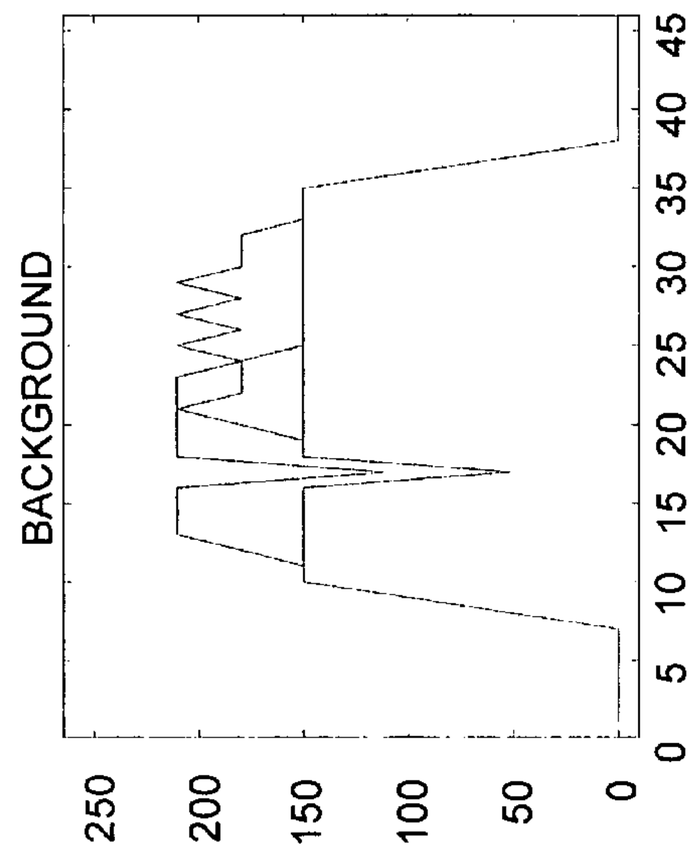

FIG. 4C

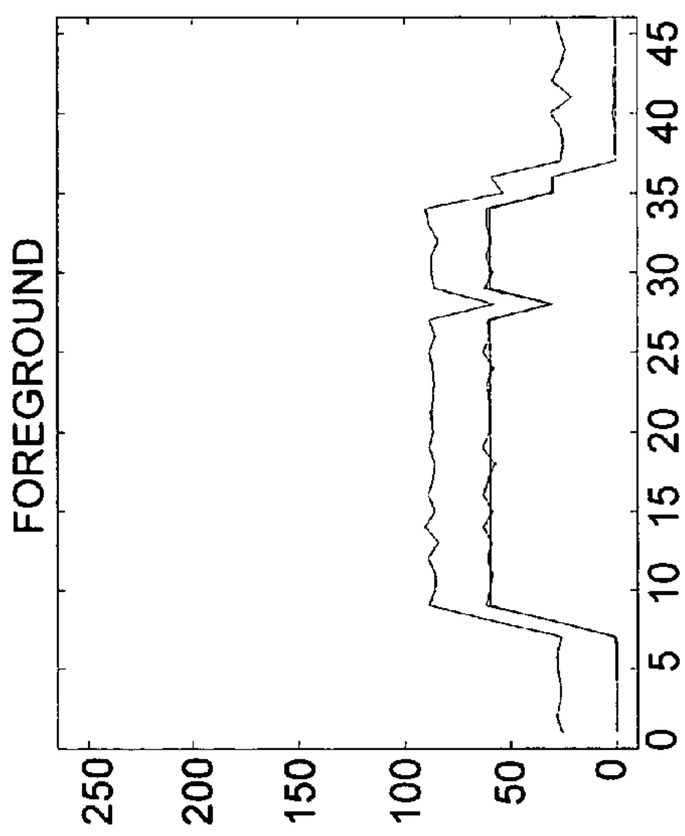

FIG. 3E

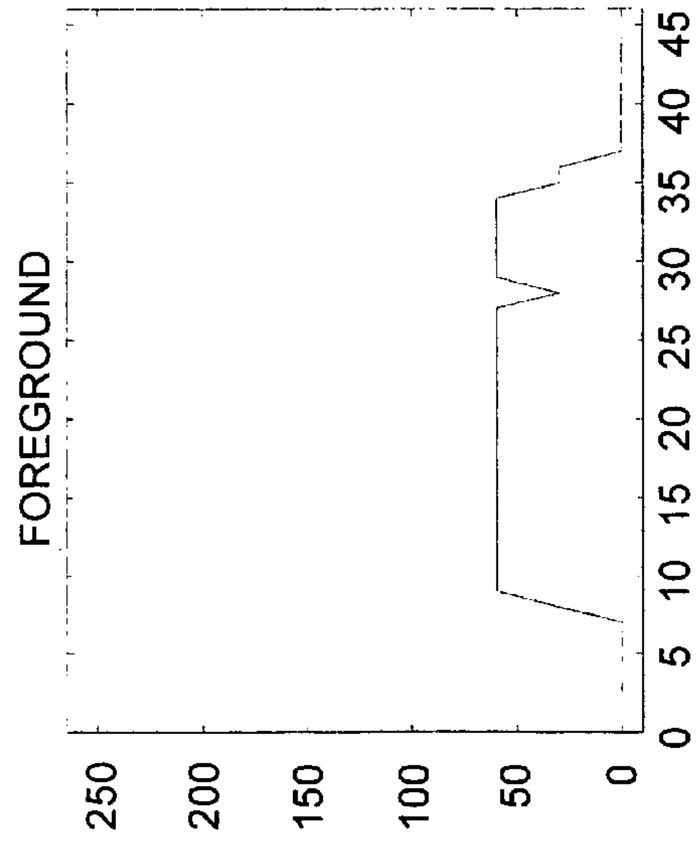

FIG. 4B

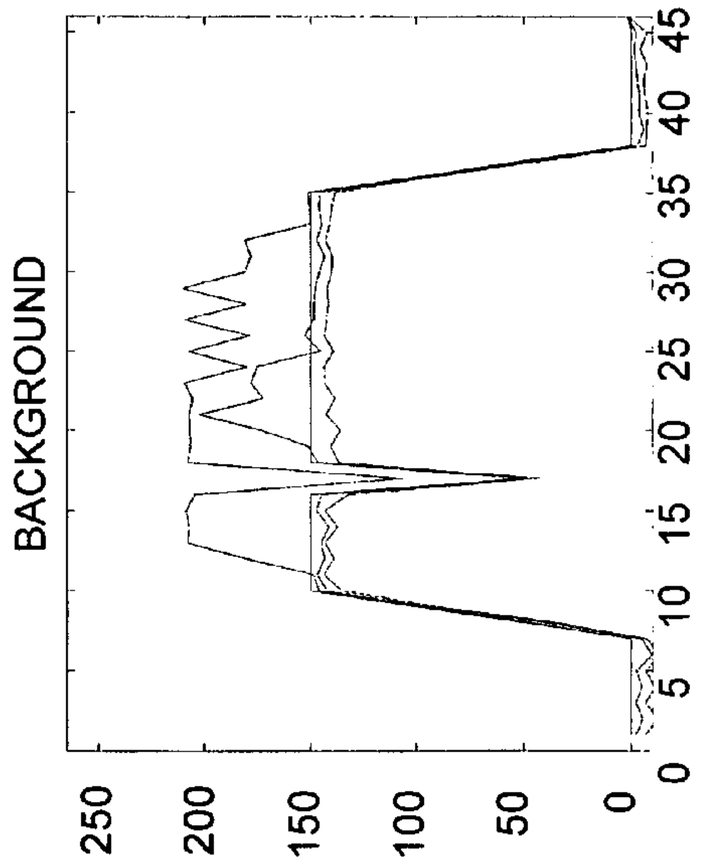

FIG. 4E

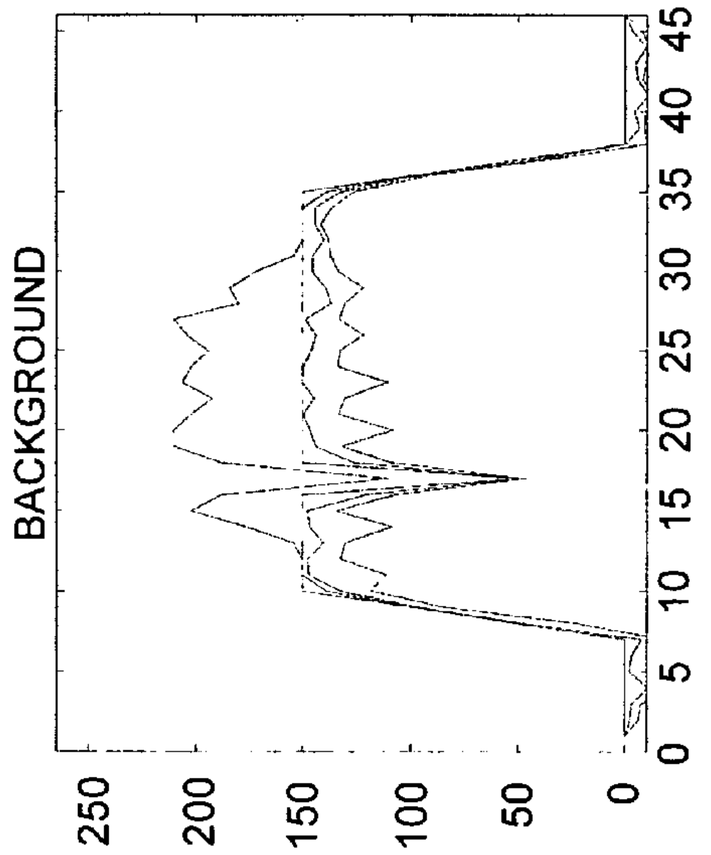

FIG. 4G

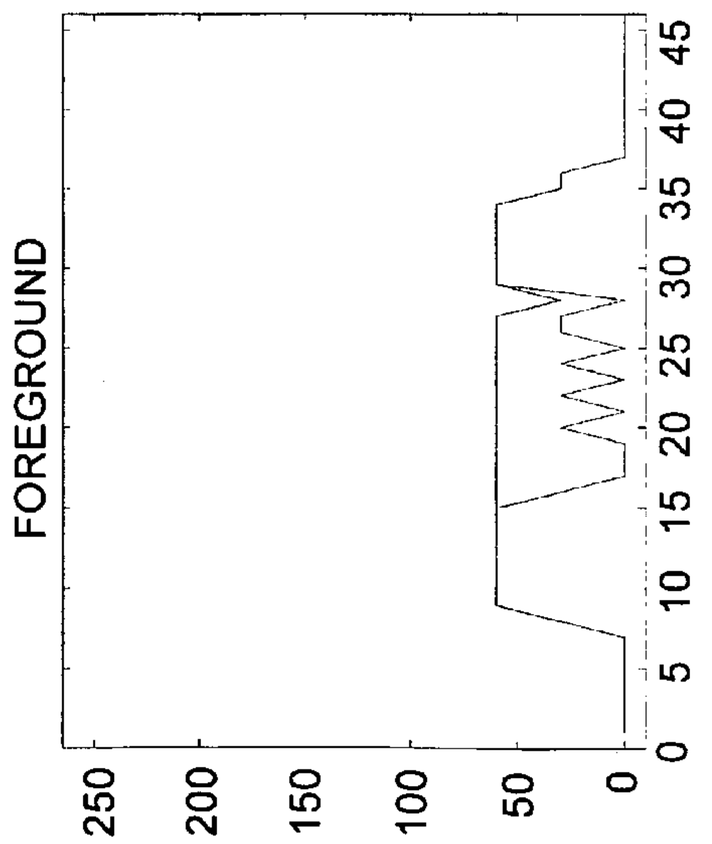

FIG. 4D

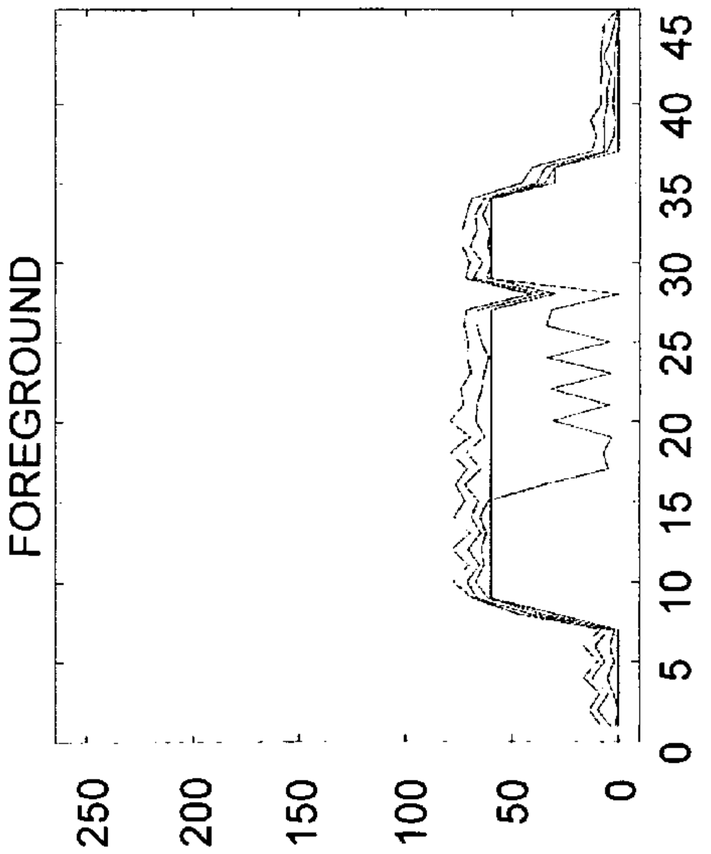

FIG. 4F

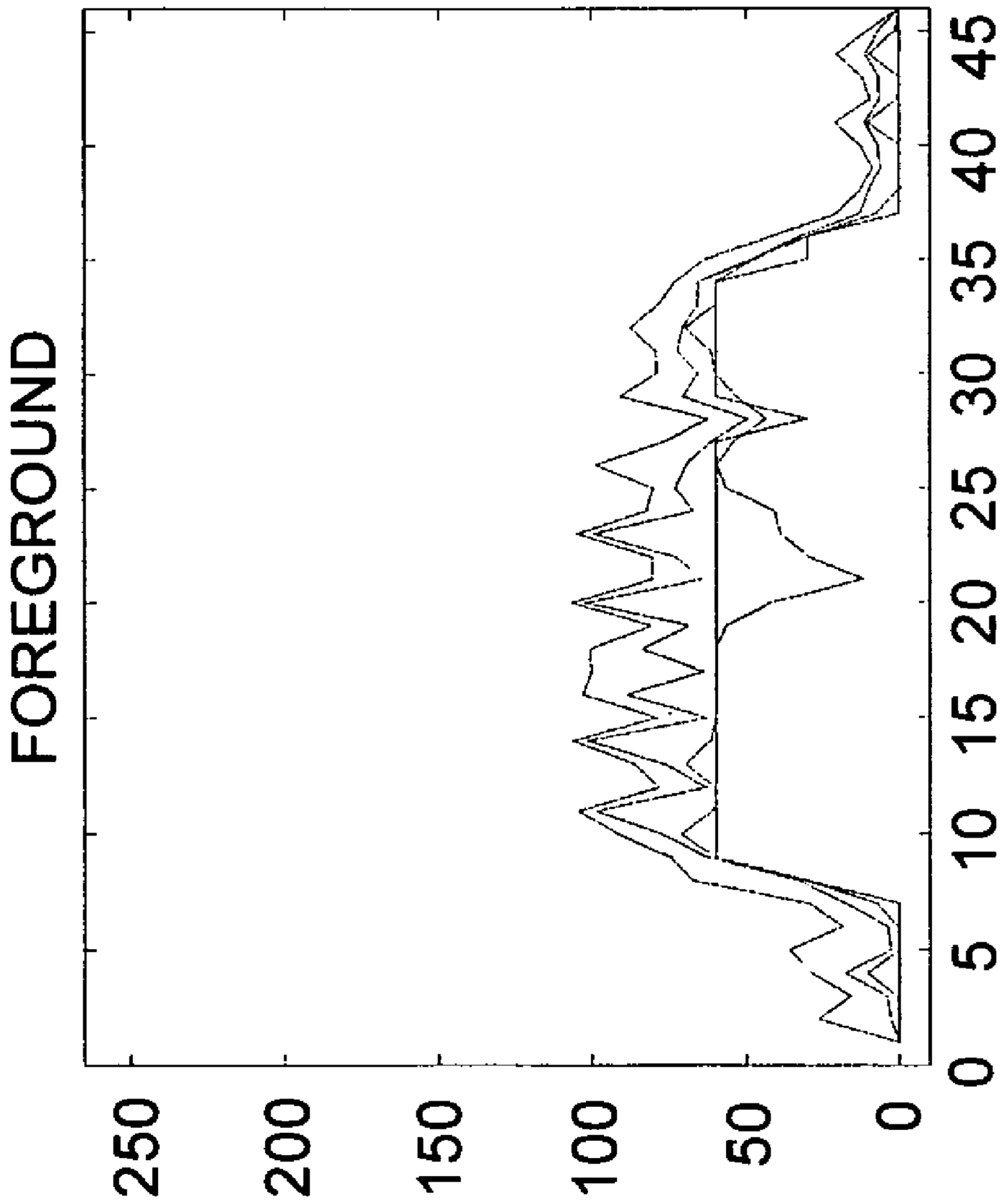

FIG. 4H

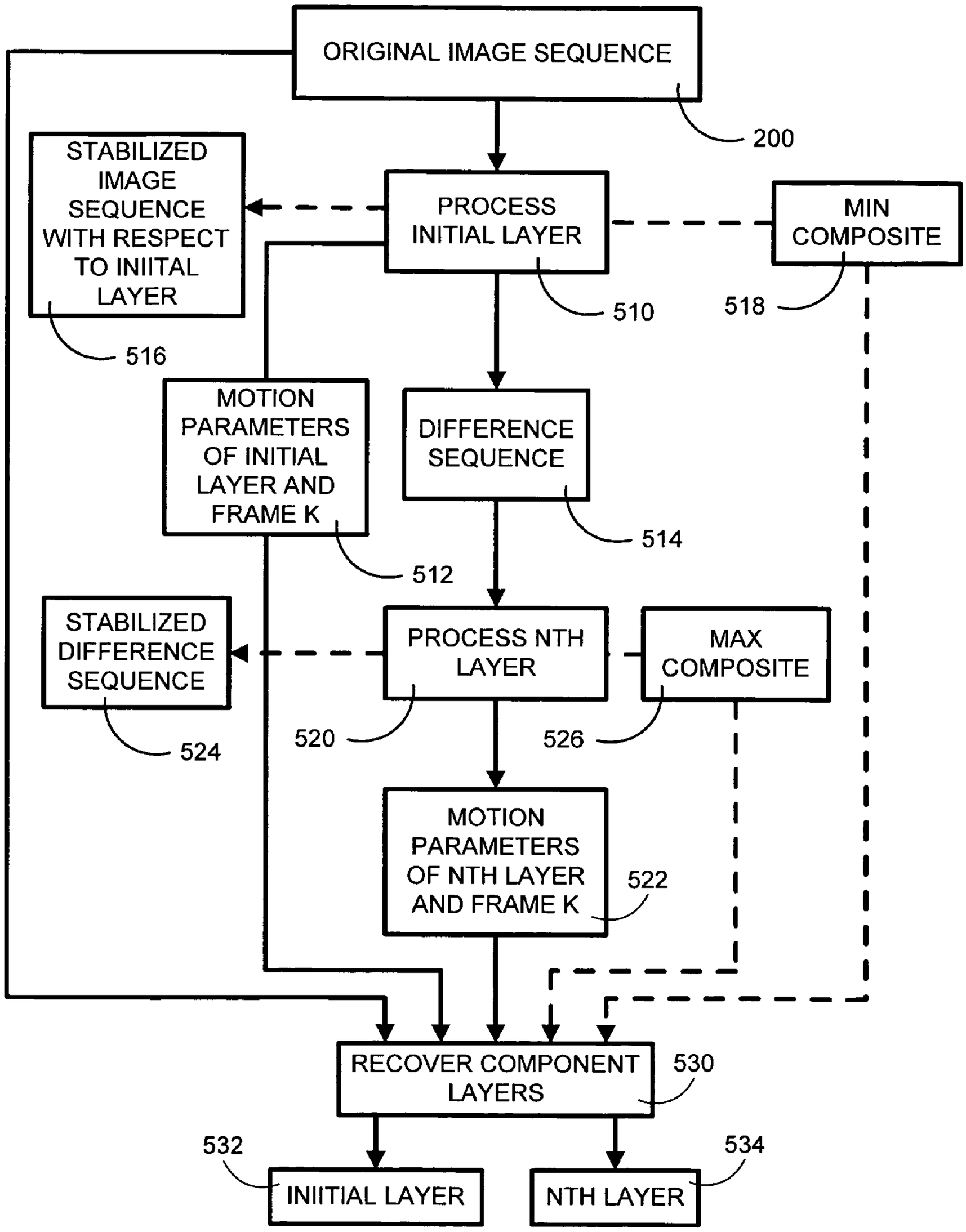
ORIGINAL IMAGE SEQUENCE
200
STABILIZED IMAGE SEQUENCE WITH RESPECT TO INIITAL LAYER
516
PROCESS INITIAL LAYER
510
MIN COMPOSITE
518
MOTION PARAMETERS OF INITIAL LAYER AND FRAME K
512
DIFFERENCE SEQUENCE
514
STABILIZED DIFFERENCE SEQUENCE
524
PROCESS NTH LAYER
520
MAX COMPOSITE
526
MOTION PARAMETERS OF NTH LAYER AND FRAME K
522
RECOVER COMPONENT LAYERS
530
532
INIITIAL LAYER
534
NTH LAYER

FIG. 5

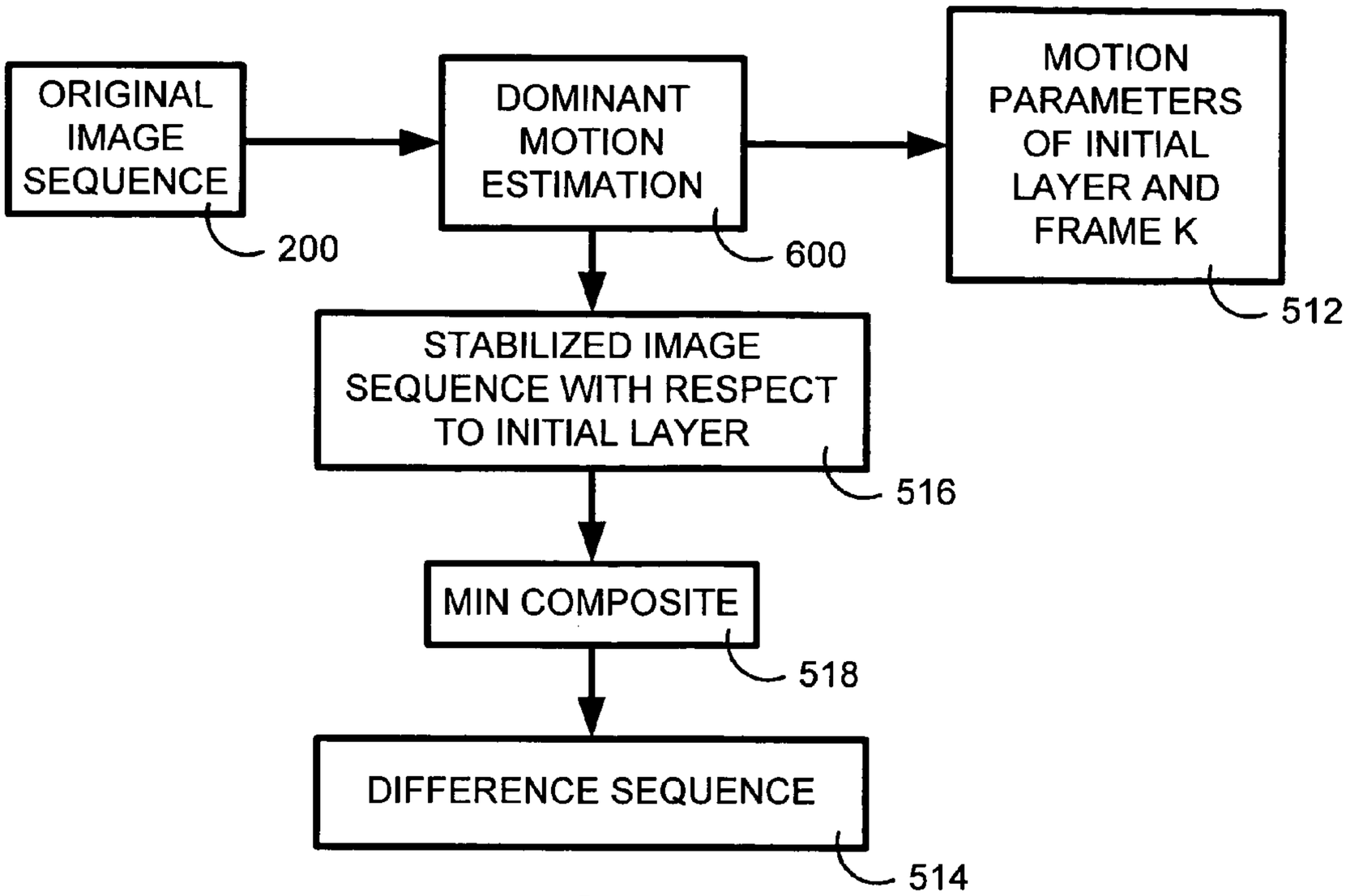
ORIGINAL IMAGE SEQUENCE
200
DOMINANT MOTION ESTIMATION
600
MOTION PARAMETERS OF INITIAL LAYER AND FRAME K
512
STABILIZED IMAGE SEQUENCE WITH RESPECT TO INITIAL LAYER
516
MIN COMPOSITE
518
DIFFERENCE SEQUENCE
514

FIG. 6

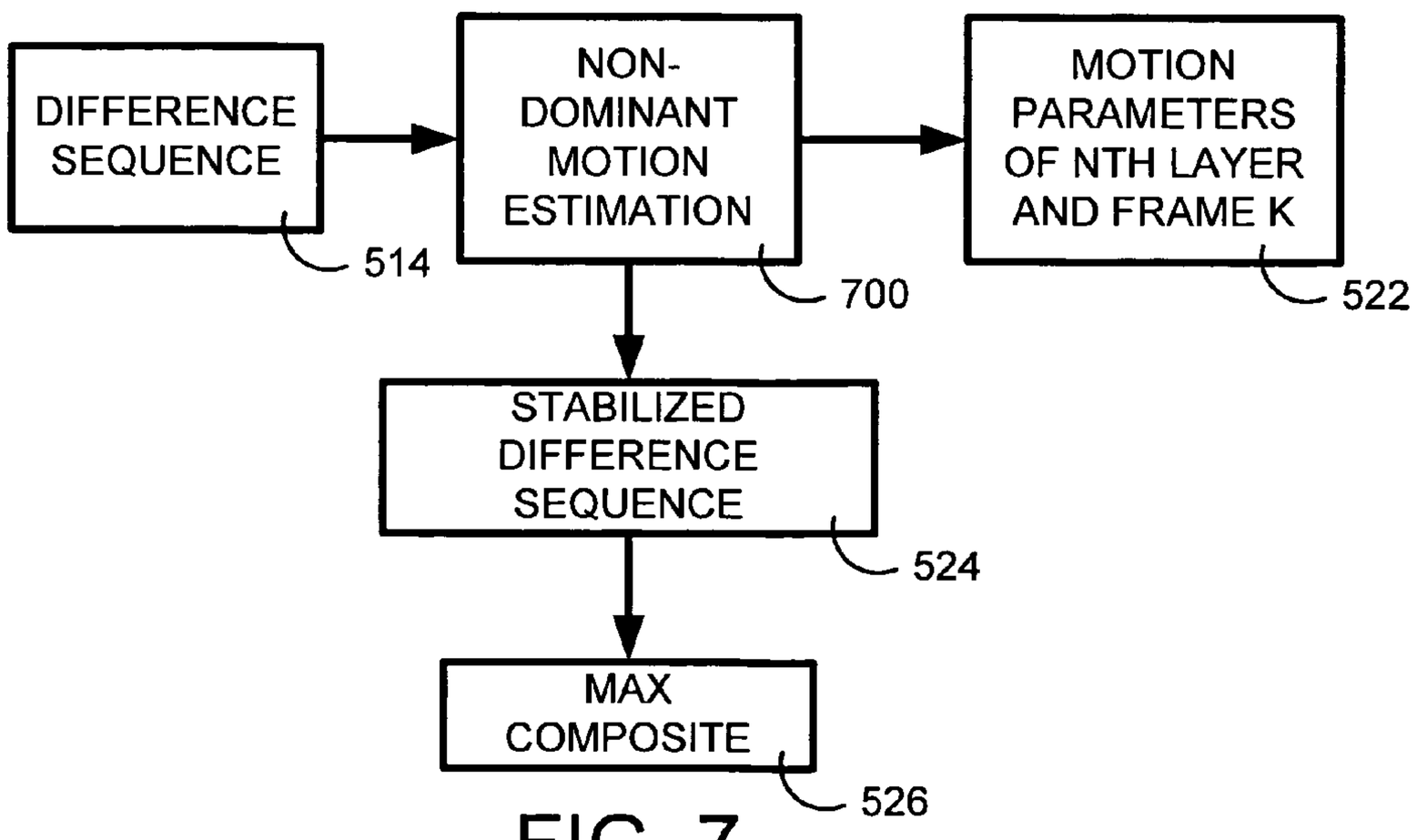
DIFFERENCE SEQUENCE
514
NON-DOMINANT MOTION ESTIMATION
700
MOTION PARAMETERS OF NTH LAYER AND FRAME K
522
STABILIZED DIFFERENCE SEQUENCE
524
MAX COMPOSITE
526

FIG. 7

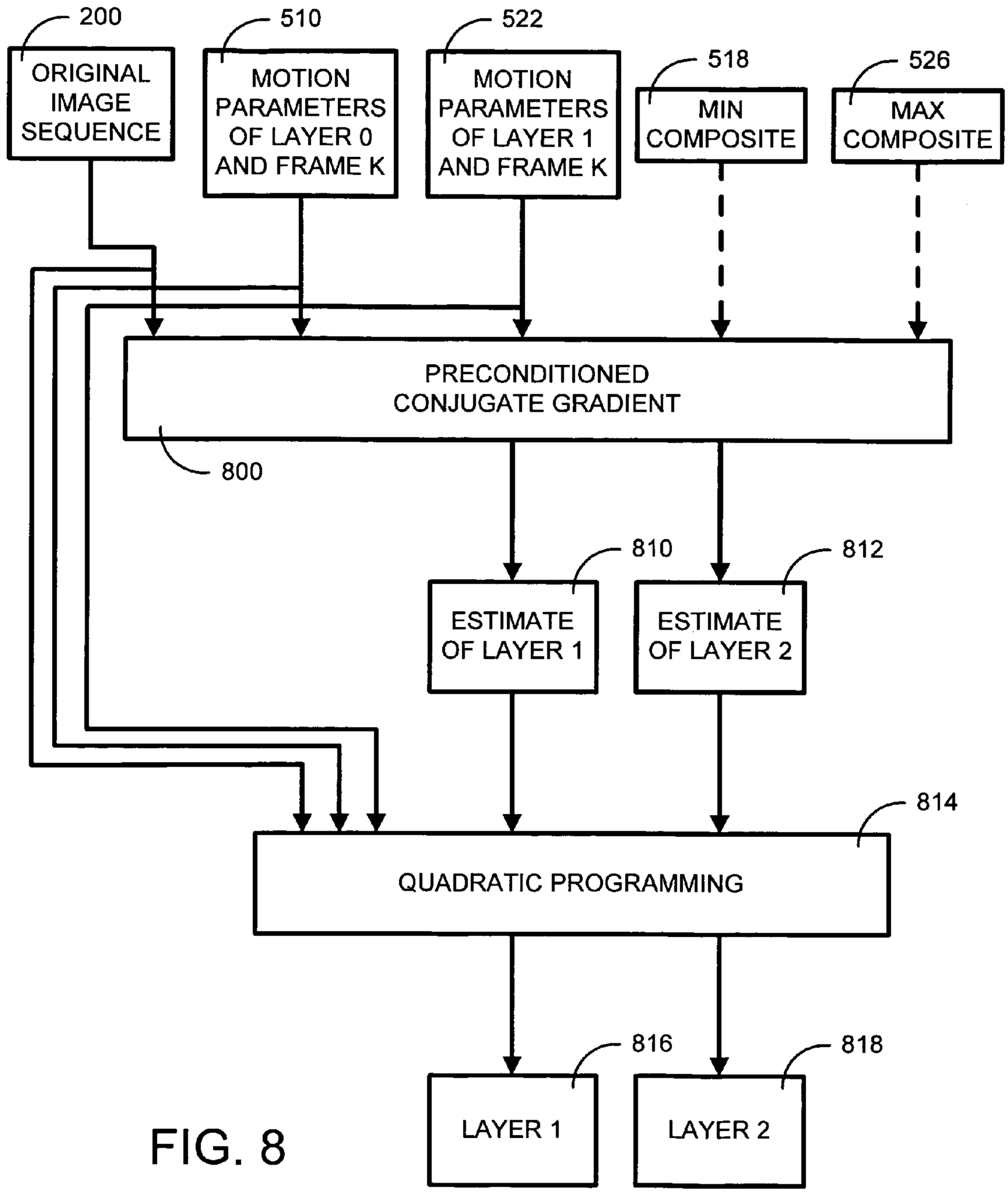
200
ORIGINAL IMAGE SEQUENCE
510
MOTION PARAMETERS OF LAYER 0 AND FRAME K
522
MOTION PARAMETERS OF LAYER 1 AND FRAME K
518
MIN COMPOSITE
526
MAX COMPOSITE
PRECONDITIONED CONJUGATE GRADIENT
800
810
ESTIMATE OF LAYER 1
812
ESTIMATE OF LAYER 2
814
QUADRATIC PROGRAMMING
816
LAYER 1
818
LAYER 2

FIG. 8

SYSTEM AND METHOD FOR EXTRACTING REFLECTION AND TRANSPARENCY LAYERS FROM MULTIPLE IMAGES

BACKGROUND OF THE INVENTION

1. Field of the Invention

The present invention relates in general to stereo reconstruction, and in particular, to a system and method for extracting structure from multiple images of a scene by representing the scene as a group of image layers, including reflection and transparency layers.

2. Related Art

Many natural images contain mixtures of reflected (reflections) and transmitted light (transparencies). Many natural images will typically contain one or both, i.e., contain mixtures of reflected and transmitted light. For example, shiny or glass-like surfaces typically create a reflected image of other surfaces in its immediate environment. Also, surfaces like glass and water are (at least partially) transparent, and hence will transmit the light from the surfaces behind it. Although it should be noted that the transmitted light is usually attenuated to some degree by the glass (or frontal surface), and thus, the notion of partial transparency or "translucency" is more general. However, following common usage in the field, the term "transparency" is used to indicate both complete transparency and translucency.

As such, many natural images are composed of reflected and transmitted images, which are super-imposed on each other. When viewed from a moving camera, these component layer images appear to move relative to each other. Techniques to recover the multiple motions are commonly referred to as multiple motion recovery techniques. The problem of multiple motion recovery and the reflection and transmission of light on surfaces in visual images has been addressed in several physics-based vision studies. Likewise, a number of techniques for recovering multiple motions from image sequences have been developed.

These techniques can recover multiple motions even in the presence of reflections and transparency. A subclass of these techniques also extract the individual component layer image from the input composite sequence, but only in the absence of reflections and transparency (i.e., all the layers are opaque). Although several studies locked onto each component motion, they actually created a "reconstructed" image of each layer through temporal integration and fell short of being a proper extraction of the component layers. This is because the other layers were not fully removed, but rather appeared as blurred streaks.

The detection of transparency in single images has been studied, but these studies do not provide a complete technique for layer extraction from general images. Thus, current and previous systems have not demonstrated how to accurately recover the component images themselves and the extraction of component layers images in the presence of reflections and transparency remains a problem. Therefore, what is needed is an optimal approach to recovering layer images and their associated motions from an arbitrary number of composite images. Also, there is a need for techniques that estimate the component layer images given known motion estimates.

SUMMARY OF THE INVENTION

To overcome the limitations in the prior art described above, and to overcome other limitations that will become apparent upon reading and understanding the present specification, the present invention is embodied in a system and method for extracting structure from multiple images of a scene by representing the scene as a group of image layers, including reflection and transparency layers.

In general, the present invention performs layer extraction from multiple images containing reflections and transparencies. The present invention includes an optimal approach for recovering layer images and their associated motions from an arbitrary number of composite images. The present invention includes image formation equations, the constrained least squares technique used to recover the component images, a novel method to estimate upper and lower bounds on the solution using min- and max-composites, and a motion refinement method.

Specifically, the present invention includes two different techniques for estimating the component layer images given known motion estimates. The first approach uses constrained least squares to optimally recover the layer images. The second approach iteratively refines lower and upper bounds on the layer images using two novel compositing operations, namely minimum and maximum composites of aligned images. These layer extraction techniques are combined with a dominant motion estimator and a subsequent motion refinement stage. This produces a completely automated system that recovers transparent images and motions from a collection of input images.

In one embodiment, the present invention involves first computing a primary motion estimate, second estimating a primary layer associated with the primary motion estimate, third computing a secondary motion estimate, fourth estimating a secondary layer associated with the secondary motion estimate and then iteratively refining lower and upper bounds on the primary and secondary layers to estimate the layers. In another embodiment motion estimates are improved by using motion re-estimation. Also, estimating the layers can be accomplished by using constrained least squares to optimally recover the layer images.

The present invention as well as a more complete understanding thereof will be made apparent from a study of the following detailed description of the invention in connection with the accompanying drawings and appended claims.

BRIEF DESCRIPTION OF THE DRAWINGS

Referring now to the drawings in which like reference numbers represent corresponding parts throughout:

FIG. **1** is a block diagram illustrating an apparatus for carrying out the invention;

FIG. **2** is an overview block diagram of the present invention;

FIGS. **3**A–**3**E show a constrained least square illustration using a one-dimensional example;

FIGS. **4**A–**4**H show a min/max alternation illustration using a one-dimensional example;

FIG. **5** shows the operational and functional details of the present invention;

FIG. **6** shows additional details for processing the first layer of FIG. **3** of the present invention;

FIG. **7** shows additional details for processing the second layer of FIG. **3** of the present invention; and

FIG. **8** shows additional details for recovering component images of FIG. **3** of the present invention.

DETAILED DESCRIPTION OF THE INVENTION

In the following description of the invention, reference is made to the accompanying drawings, which form a part hereof, and in which is shown by way of illustration a specific example in which the invention may be practiced. It is to be understood that other embodiments may be utilized and structural changes may be made without departing from the scope of the present invention.

I. Exemplary Operating Environment

FIG. **1** and the following discussion are intended to provide a brief, general description of a suitable computing environment in which the invention may be implemented. Although not required, the invention will be described in the general context of computer-executable instructions, such as program modules, being executed by a computer. Generally, program modules include routines, programs, objects, components, data structures, etc. that perform particular tasks or implement particular abstract data types. Moreover, those skilled in the art will appreciate that the invention may be practiced with a variety of computer system configurations, including personal computers, server computers, hand-held devices, multiprocessor systems, microprocessor-based or programmable consumer electronics, network PCs, minicomputers, mainframe computers, and the like. The invention may also be practiced in distributed computing environments where tasks are performed by remote processing devices that are linked through a communications network. In a distributed computing environment, program modules may be located on both local and remote computer storage media including memory storage devices.

With reference to FIG. **1**, an exemplary system for implementing the invention includes a general purpose computing device in the form of a conventional computer **100**, including a processing unit **102**, a system memory **104**, and a system bus **106** that couples various system components including the system memory **104** to the processing unit **102**. The system bus **106** may be any of several types of bus structures including a memory bus or memory controller, a peripheral bus, and a local bus using any of a variety of bus architectures. The system memory includes computer storage media in the form of read only memory (ROM) **110** and random access memory (RAM) **112**. A basic input/output system **114** (BIOS), containing the basic routines that helps to transfer information between elements within computer **100**, such as during start-up, is stored in ROM **110**. The computer **100** may include a hard disk drive **116** for reading from and writing to a hard disk, not shown, a magnetic disk drive **118** for reading from or writing to a removable magnetic disk **120**, and an optical disk drive **122** for reading from or writing to a removable optical disk **124** such as a CD ROM or other optical media. The hard disk drive **116**, magnetic disk drive **128**, and optical disk drive **122** are connected to the system bus **106** by a hard disk drive interface **126**, a magnetic disk drive interface **128**, and an optical drive interface **130**, respectively. The drives and their associated computer-readable media provide storage of computer readable instructions, data structures, program modules and other data for the computer **100**. Although the exemplary environment described herein employs a hard disk, a removable magnetic disk **120** and a removable optical disk **130**, it should be appreciated by those skilled in the art that other types of computer readable media can store data that is accessible by a computer. Such computer readable media can be any available media that can be accessed by computer **100**. By way of example, and not limitation, such computer readable media may comprise communication media and computer storage media. Communication media typically embodies computer readable instructions, data structures, program modules or other data in a modulated data signal such as a carrier wave or other transport mechanism and includes any information delivery media. The term "modulated data signal" means a signal that has one or more of its characteristics set of changed in such a manner as to encode information in the signal. By way of example, and not limitation, communication media includes wired media such as wired network or direct wired connection, and wireless media such as acoustic, RF, infrared and other wireless media. By way of example, and not limitation, communication media includes wired media such as a wired network or direct wired connection, and wireless media such as acoustic, RF, infrared and other wireless media. Computer storage media includes any method or technology for the storage of information such as computer readable instructions, data structures, program modules or other data. By way of example, such storage media includes RAM, ROM, EPROM, flash memory or other memory technology, CD-ROM, digital video disks (DVD) or other optical disk storage, magnetic cassettes, magnetic tape, magnetic disk storage or other magnetic storage devices, or any other medium which can be used to store the desired information and which can be accessed by computer **100**. Combinations of any of the above should also be included within the scope of computer readable media.

A number of program modules may be stored on the hard disk, magnetic disk **120**, optical disk **124**, ROM **110** or RAM **112**, including an operating system **132**, one or more application programs **134**, other program modules **136**, and program data **138**. A user may enter commands and information into the computer **100** through input devices such as a keyboard **140** and pointing device **142**. Other input devices (not shown) may include a microphone, joystick, game pad, satellite dish, scanner, or the like. These and other input devices are often connected to the processing unit **102** through a serial port interface **144** that is coupled to the system bus **106**, but may be connected by other interfaces, such as a parallel port, game port or a universal serial bus (USB). A monitor **146** or other type of display device is also connected to the system bus **106** via an interface, such as a video adapter **148**. In addition to the monitor **146**, computers may also include other peripheral output devices (not shown), such as speakers and printers.

The computer **100** may operate in a networked environment using logical connections to one or more remote computers, such as a remote computer **150**. The remote computer **150** may be a personal computer, a server, a router, a network PC, a peer device or other common network node, and typically includes many or all of the elements described above relative to the personal computer **100**, although only a memory storage device **152** has been illustrated in FIG. **1**. The logical connections depicted in FIG. **1** include a local area network (LAN) **154** and a wide area network (WAN) **156**. Such networking environments are commonplace in offices, enterprise-wide computer networks, intranets and Internet.

When used in a LAN networking environment, the computer **100** is connected to the local network **154** through a network interface or adapter **158**. When used in a WAN networking environment, the computer **100** typically includes a modem **160** or other means for establishing communications over the wide area network **156**, such as the Internet. The modem **160**, which may be internal or external,

is connected to the system bus **106** via the serial port interface **144**. In a networked environment, program modules depicted relative to the computer **100**, or portions thereof, may be stored in the remote memory storage device. It will be appreciated that the network connections shown are exemplary and other means of establishing a communications link between the computers may be used.

II. General Overview

FIG. **2** is an overview block diagram of the present invention. The present invention is embodied in a system and method for extracting structure from multiple images of a scene by representing the scene as a group of image layers, such as reflection and transparency layers. A scene or an original image sequence **200** can contain mixtures of reflected (reflections) and transmitted light (transparencies) as component layers **212**, **214** (a primary layer **212** and n layers **214**), which can be super-imposed on one another. When viewed from a moving camera, these component layers **212**, **214** can appear to move relative to each other to create multiple motions.

As such, it is desirable to extract the component layers **212**, **214** in the presence of any reflections and transparencies and recover the multiple motions. The present invention accurately extracts the component image layers **212**, **214** and then recovers their associated motions from an arbitrary number of composite images. Extracting structure from multiple images of the scene **200** by representing the scene as a group of image component layers **212**, **214** is accomplished by the systems and methods described below.

In general, first, a primary motion estimate is computed (step **220**) for the scene **200**. Second, based on this primary motion estimate, a primary layer associated with the primary motion estimate is determined (step **222**). Third, the scene **200** is analyzed and a secondary motion estimate is computed (step **224**). Fourth, a secondary layer associated with the secondary motion estimate is estimated (step **226**) based on the secondary motion estimate. Next, the primary and secondary layers are recovered by iteratively refining lower and upper bounds on the primary and secondary layers (step **228**). Although the above description and the description that follows refer to primary and secondary layers (or dominant and non-dominant layers), it should be noted that more than two layers could be recovered by the present invention.

In addition, once the motion is known or for the case when the input composite images can be modeled as an additive mixture of the component layers (such a model applies when the light from one surface is reflected by another), a constrained least-square technique can be used to recover the layers from the known motions. It should be noted that this case applies to an arbitrary number of layers. Further, a complete technique that combines the layer extraction step together with an automatic multiple motion technique to recover the layers and their motions from the input images is preferably used.

In this case, for a complete solution, first, a dominant motion (for example, of the desired layer) for the sequence is computed using image alignment against a current min-composite. Second, a difference image calculation is computed between stabilized images and the min-composite. Third, non-dominant motion is computed by aligning the difference image calculation with a max-composite of the images. Fourth, initial layer estimates of the dominant and non-dominant motion estimates are used and the motion estimates are improved using motion re-estimation. Last, unconstrained least-squares are computed as an initial value and positivity constraints are used to solve a quadratic related to the layer extraction. The embodiments described above are provided as high level descriptions of the general operation of the present invention and will be discussed in detail below.

III. Details of the Components and Operation

A. Image Formation:

This section presents the general problem formulation, including the image formation equations. In "Ordinal characteristics of transparency", *AAAI-90 Work Qualitative Vision*, pp. 77–81, 1990, by E. H. Adelson and P. Anandan a recursive process was proposed as the generative model for obtaining a composite image from component layers. At each pixel, assuming a given spatial ordering of layers relative to the viewpoint, each layer partially attenuates the total amount of light coming from all the layers "behind it" and adds its own light to give an output signal. The final composite image is the result of applying this process to all layers in a back to front fashion. This process can be summarized in terms of the following modified form of the over operator used in image compositing, as described by J. F. Blinn. Jim Blinn's corner: in "Compositing, part 1: Theory", *IEEE Comp. Gr. and Appl.,* 14(5): 83–87, September 1994,

$$F \wedge B \equiv F + (1-\alpha_F)B, \tag{1}$$

where F and B denote the colors of the foreground and the background images. The standard definition of the over operator uses foreground colors that are premultiplied by the opacities of the foreground layer, hence, the R, G, and B values that must be $\leqq\alpha$. In this case, this restriction is removed in areas of reflection, in order to handle additive composition.

For the purposes of the present invention, it is assumed that each component layer (indexed by l=0, . . . L−1) is defined by a signal or 2D image $f_l(x)$, (where f_l denotes layer l and x will is used to index both 1-D signals and 2-D images), which is warped to the current image (indexed by k) coordinate system via a warping operator W_{kl}, which resamples the pixels. Also, $W_{kl}{}^o f_l$ denotes the warped image. Hence, the composite image (or the original image sequence) is given by the equation:

$$m_k = W_{k0}{}^o f_0 \ldots W_{k(L-1)}{}^o f_{L-1} \tag{2}$$

Next, it is assumed that W_{kl} is an invertible global parametric motion (where W_{kl} denotes the motion parameters of layer l and frame k), such as translation, rotation, affine, or perspective warp. Also, it is initially assumed that the W^{kl} are known (it should be noted that this assumption is removed in Section III. D below).

Image formation and pure additive mixing of images can be expressed as:

$$m_k(x) = \sum_{l=0}^{L-1} W_{kl}^o f_l(x). \tag{3}$$

An alternative way of writing the image formation equations is to look at the discrete image pixels written in (rasterized) vector form,

$$m_k = \sum_{l=0}^{L-1} W_{kl} f_l. \tag{4}$$

The above formula is equivalent to the first (continuous) formula if the images are sampled without aliasing (below their Nyquist frequency) and the warping does not unduly compress the layer images (thereby causing aliasing). The W_{kl} matrices are very sparse, with only a few non-zero coefficients in each row (i.e., the interpolation coefficients for a given pixel sample). In addition to the image formation equations, it is known that the original layer images are non-negative, i.e., $f_l(x) \geqq 0$. As will be described below, this provides very important (and useful) constraints on the solution space.

For real images, there is a chance that the images may be saturated (i.e., $m_k(x)=255$ for 8-bit images) in some regions. An accurate model of the mixing process can be generated with a photo-metrically calibrated camera, i.e., cameras where the radiance to pixel-value transfer curve is known, as described by Paul E. Debevec and Jitendra Malik, in "Recovering high dynamic range radiance maps from photographs", *SIGGRAPH'97*, pp. 369–378, August 1997. For the description that follows, however, it is assumed that the mixing process is linear, but that the observed mixed signal values m_k are clipped to 255. The extension to a truly calibrated camera is straightforward, but may require a level-dependent noise process to be added.

B. Recovering Component Images with Constrained Least Squares

This section presents the constrained least squares algorithm that is used to recover the component images and that was described generally above. Given a set of images m_k, the layer images f_l can be recovered. Since the image formation equations are linear, constrained least squares,

$$\min \sum_k \left\| \sum_{l=0}^{L-1} W_{kl} f_l - m_k \right\|^2 \quad s \cdot t \cdot f_l \geq 0, \tag{5}$$

can be used. Such a least squares estimator is statistically optimal if the measured input images are corrupted by uniform independent (white) Gaussian noise. The least squares problem is constrained, since it is required that all of the elements in the f_l images be non-negative. Also, for any pixel in m_k that is saturated (255), only the mismatch between m_k and the mixed layers is penalized if the predicted value is below 255.

This least squares problem is very large (one term or linear equation per measured input pixel), and very sparse (only a few non-zero coefficients per equation). Iterative techniques, such as variants of gradient descent or conjugate gradient, should be used. For instance, for a 1-D signal, it should be usually possible to form a narrow-banded problem by interleaving the layer pixel. These 1D examples will be discussed below for illustrative purposes.

For the current implementation of the present invention, a two stage approach is preferably used for solving the constrained least-squares problem and is discussed with the entire system with reference to FIGS. **5–8** below. Generally, first, the problem is solved without constraints using a Preconditioned Conjugate Gradient (PCG) method. Any standard mathematical technical computing environment for combining, for example, numeric computation, advanced graphics and visualization, and a high-level programming language can be used. The mathematical computing environment can have functions for the PCG for data analysis and visualization, numeric and symbolic computation, engineering and scientific graphics, modeling, simulation, and prototyping, programming, application development, and GUI design. Using the PCG method as an initial estimate, a Quadratic Programming (QP) technique can be used with the positivity constraints enabled (again using a standard function in the mathematical technical computing environment) to obtain the constrained optimal solution.

The constrained least-square problem posed in Equation 5 has a unique solution unless the set of relative motions between the component layers in the input composites is degenerate (or poorly conditioned) in some fashion. Under the general (non-degenerate) condition, given known motion, the component layers from the input composites can be recovered. In practice, although it is usually not assumed that the motions are known, indeed the estimation of the motion is an important part of the overall technique. This will be discussed further in sections III. D.

Namely, the positivity constraints on the component signals (images) restrict the solution to be in a convex subspace. Therefore, the quadratic programming program posed in Equation 5 does not suffer from multiple local minima. Without the constraints, the solution is not unique. This can be seen even without analyzing the particular structure of the W_{kl} matrices, based on the following reasoning. If $\{f\}$ is a set of component layer signals (images) that minimizes the least-squares error defined in Equation 5, since each input image is simply a sum of warped and resampled versions of these components, a constant image can be subtracted to one of the layers. This amount can be distributed (added) among the other layers without changing the sum. The new set of layer thus obtained is also a valid solution to the unconstrained minimization problem posed in Equation 5. This implies that the system of equations is degenerate.

FIGS. **3**A–E illustrate this degeneracy, using a one-dimensional example. FIGS. **3**A and **3**B show the plots of the two input component layers. Five mixed signals were created by shifting these two relative to each other by different (known) amounts and adding random Gaussian noise. As an example, one of these five mixed signals is shown in FIG. **3**C. The solid curves in FIGS. **3**D and **3**E show the recovered component layers signals obtained by solving the unconstrained least-squares problem, using a "pseudo-inverse" (minimum norm) technique. Note that the recovered signal (solid line) is offset from the true signal (similar results are obtained in the noise-free case as well). For the two layer case, the amount of this offset is equal to half the difference between the mean foreground and background layers values.

In practice, this degeneracy is not too critical, since it leads to simply a DC offset of the signals. Moreover, if each layer has at least one pixel that is black (i.e., signal value of zero), this degeneracy can be removed using the positivity constraint. This is because subtracting an offset from any of the layers will lead to at least one negative valued pixel, which violates the positivity constraint. The result of solving the constrained least-square problem is shown as the upper curve in FIG. **3**D and the lower curve in FIG. **3**E. As shown,

these reconstructed signals differ from the input signals only by small random noise. In other words, solving the optimization problem with constraints appears to fix the degeneracy in the system. It should be noted, however, if there is some layer that has no black pixel (i.e., $f_l \geqq c$, where $c>0$), the solution can only be determined up to an offset of c.

In practice, in 2D images, there may also be additional source of degeneracy or poor conditioning due to the structure of the warping matrix W_{kl}. In the case when the relative motion between the component layers consists of shifts purely in the horizontal (or vertical) direction. In this case, the overall problem decouples into a set of independent problems corresponding to each row (or column). Each row will be determined only up to an arbitrary but different DC offset. To impose the positivity constraint and obtain a unique solution, each row in each layer must have a black pixel, which may be unrealistic. Hence, even the use of the positivity constraints may not guarantee the correct recovery of component layers. In summary, the constrained least-square problem posed in Equation 5 has a unique solution unless the set of relative motions between the component layers in the input composites is degenerate (or poorly conditioned) in some fashion, as discussed above.

C. Estimating Upper and Lower Bounds with Min/Max Alternation

This section illustrates estimating upper and lower bounds on the solution using min- and max-composites. In order to run the constrained least-squares algorithm, the motions for all of the layers must be known. Unfortunately, in many image sequences, only the dominant motion can be reliably estimated at first. Thus, estimating the non-dominant motion (s) is important to the overall problem. In this section, a novel algorithm is proposed that iteratively re-estimates upper and lower bounds on two component layers. This estimation can be interleaved with layer motion estimation.

The present technique is based on the following observation. Once the dominant motion has been estimated, an estimate for the layer corresponding to this motion can be obtained by forming a mosaic from the stabilized image sequence. However, unlike conventional mosaics, where either an average or median is used to form the estimate (sometimes with appropriate feathering near the edges), the present invention computes the minimum pixel value across all images in the stabilized sequence.

The min-composite estimate is computed because the contributions from other layers can only add to the intensity at a given pixel. Therefore, the min across all mixed images gives an upper bound on the possible value for the dominant layer. More formally, let

$$s_k = W_{k0}^{-1} m_k = f_0 + \sum_{l=1}^{L-1} W_{k0}^{-1} W_{kl} f_l \tag{6}$$

be the set of images stabilized with respect to layer **0**. Then,

$$f_0^{\max} \min_k s_k = f_0 + \sum_{l=1}^{L-1} \min_k W_{k0}^{-1} W_{kl} f_l \tag{7}$$

is an upper bound on f_0.

Once an estimate for layer **0** is found, the difference images can be computed

$$d_k = s_k - f_0^{max.} \tag{8}$$

These difference images give the luminance that is accounted for by the other layers (where s_k denotes the stabilized image sequence with respect to layer **0**, f_0^{max} denotes the MIN composite and d_k denotes the difference sequence).

Now, distributing this residual error among the remaining layers is important. For this reason, the two layer (foreground/background) case is described. This is not a big limitation in practice, since multiple reflections/transmissions are relatively rare.

In the two layer case, the difference images d_k are a partial estimate (lower bound) on the amount of light in layer **1**. These images can be stabilized using a parametric motion estimator (assuming that the motion is not known a priori), and thereby compute W_{kl}. Let

$$t_k = W_{kl}^{-1} W_{k0} d_k - f_l + W_{kl}^{-1} W_{k0} (f_0 - f_0^{max}). \tag{9}$$

be the set stabilized of difference images. A max-composite can then be computed of the stabilized differences,

$$f_1^{\min} = \max_k t_k = f_1 + \max_k W_{kl}^{-1} W_{k0} (f_0 - f_0^{\max}). \tag{10}$$

Since $f_0 - f_0^{max} \leqq 0$, each t_k is an underestimate of f_l, and f_l^{min} is the tightest lower bound on f_l it can be computed (where t_k denotes the stabilized difference sequence, and f_l^{min} denotes the MAX composite).

With the improved lower bound estimate for f_l (it should be noted that $f_l \geqq 0$ was an initial value), a better estimate (tighter upper bound) for f_0 can be recomputed. Instead of stabilizing the original input images m_k, the corrected images can be stabilized

$$c_k = m_k - W_{kl} f_l^m \tag{11}$$

to obtain

$$s_k = W_{k0}^{-1} c_k = f_0 + W_{k0}^{-1} W_{kl} (f_l - f_l^{min}) \tag{12}$$

The amount of overestimate in each stabilized image s_k is now proportional to the difference between the lower bound on f_l and its true value.

Thus, an improved estimate for f_0^{max} can be obtained, and this can be used to obtain an improved estimate for f_0^{min}. This iteration eventually leads to the correct solution. Under ideal conditions (to be defined below), the min/max alternation algorithm described above will compute the correct estimates for f_0 and f_l. The time required to do so depends on the diameter of the largest non-zero region in the foreground layer (f_l) divided by the diameter of the shifting operation seen in all input images (to be defined below).

For the above, it is assumed that at least one pixel in the foreground layer is zero. If not, then min/max alternation will compute the best lower bound on f_l it can (which will contain at least one zero value) and stop. Also, it is assumed that there is only one isolated region (otherwise, the above applies to each region independently). The ideal conditions mentioned above come in two parts. First, the entries in the W_{kl} and W_{kl}^{-1} matrices are non-negative and second, there is no imaging noise. The first condition is, in general, only attainable if the layers are shifted by integral amounts. The

second condition is, of course, not attainable in practice. But these ideal conditions can be compensated for, as will be discussed below.

For the improved estimate, as described above, x is set to be the coordinate of some pixel where $f_l(x)=0$. Let $x' \epsilon N(x)$ be the shift-induced neighborhood of x, i.e., the set of pixels in the m_k images that are formed using $f_l(x)$. Then, since $\min_k W_{kl} f_l(x)=0$ for any pixel in N(x), $f_0^{max}(x')=f_0(x')$, i.e., the upper bound is exact at these pixels. Further, the difference signals at these pixels is exact (the lower bound matches the true value of the shifted f_l signal). Therefore, the pixels in f_l where $x'' \epsilon N'(x')$, i.e., the pixels being re-estimated using at least one correct element in f_0, will have the correct estimated value, $f_l^{min}(x'')=f_l(x'')$.

This process will grow regions of correct estimates out from pixels in the foreground that are black. These regions can grow quickly and can eventually cover the entire image. For example, $x' \epsilon N(x)$ can be analogized as a morphological dilation operator that spreads good pixels (initially, the black ones) in f_l into good estimates of f_0. Similarly, $x'' \epsilon N'(x')$ is the morphological dilation operator that spreads good pixels in f_0 into good pixels in f_l. Each dilation operation eats away at the borders of the regions that have potentially erroneous estimates of f_0 and f_l. The number of operations required is the (outside) diameter of the largest such region divided by the (inside) diameter of the dilation operator.

FIGS. **4**C and **4**D show the results of running our min/max technique on a simple 1-D signal with ±1 shifts in x. The solid curve shows the background (and foreground) signals after 1 iteration, the dashed after 2 iterations, and the phantom curve is after 3 iterations. Note that convergence has already been achieved after 3 iterations. Also, it should be noted that the technique described above is for computing upper bounds for one layer, and lower bounds for another. The process could also be run the other way around (once motion estimates are known for both layers) to simultaneously compute upper and lower bounds.

1. Noise and Resampling

The min-max technique is powerful in that it guarantees global convergence. However, the ideal conditions mentioned above should be satisfied. When noise is present, the upper and lower bounds computed by min/max may become erroneous at each iteration, leading to a divergence away from the correct solution. This behavior can be seen in FIGS. **4**E and **4**F.

Similarly, the subpixel interpolation involved in the resampling process can also lead to a bad solution. There are two potential problems when resampling the images. The first is that some entries in the W_{kl} and W_{kl}^{-1} matrices may be negative (for a positive interpolants W_{kl} such as bilinear or B-splines, the inverse warp will have negative sidelobes). In these cases, the upper/lower bound estimates f_0^{max} and/or f^{min} computed in Equations 7 and 10 may be invalid (too tight). These errors propagate from iteration to iteration, and can eventually come up with global solutions that are invalid (that may not satisfy the constraints).

The second potential problem is that an approximation to W_{kl}^{-1} is being used. This happens quite often, for example when bi-linear or bi-cubic filtering is used in conjunction with a hardware or software perspective warping algorithm (in both directions). If in this case, while the entries in W_{kl} and W_{kl}^* (the approximate inverse) may be non-negative, Equation 7 is no longer valid. Instead, the equation should read

$$f_0^{\max} = W_{k0}^* W_{k0} f_0 + \sum_{l=1}^{L-1} \min_k W_{k0}^* w_{kl} f_1. \tag{13}$$

There is no longer any guarantee that the first term is not less than f_0. In practice, it is observed that the algorithm starts to diverge rather quickly (FIGS. **4**G and **4**H).

D. Motion Refinement: Re-Estimating the Layer Motions

This section presents the motion refinement technique of the present invention, as described in general above. Once layer estimates are found (starting with one iteration of the min/max algorithm to compute the initial dominant and non-dominant motions, and optionally followed by an initial solution of the constrained least squares), the motion estimates can be refined.

The refinement technique of the present invention is similar to parametric motion estimations. Namely, expanding equation 5 using a Taylor series in the motion parameters p_{kl}, the following is obtained

$$\sum_k \sum_x \left[\sum_{l=1}^{L-1} f_1(x_{kl}(x; p_{kl})) - m_k(x) \right]^2 \approx$$

$$\sum_k \sum_x \left[\lambda_k(x) + \sum_{l=1}^{L-1} \nabla f_1(x_{kl}(x; p_{kl})) \frac{\partial x_{kl}}{\partial p_{kl}} \nabla p_{kl} \right]^2$$

The errors $\lambda_k(x)$ are then computed (difference between predicted and observed signals). The gradients ∇f_l are computed for each layer separately, and used to compute that layer's motion.

E. Complete Solution for Estimating the Component Layer Images and their Associated Motions.

Based on the above, a complete solution can be formulated that estimates the component layer images and their associated motions, in accordance with the present invention. The complete solution can be summarized as follows with reference to FIGS. **5**–**8**:

1. Compute a dominant motion for the sequence using image alignment against the current min-composite f_0^{max}.
2. Compute the difference images d_k between the stabilized images and the min-composite f_0^{max}.
3. Compute the non-dominant motion by aligning the difference images d_k with a max-composite of these images.
4. Using the initial layer guesses, improve the motion estimates using the motion re-estimation algorithm.
5. Compute the unconstrained least-squares solution.
6. Using this result as the initial value, solve the quadratic-programming problem with the positivity constraints.
7. Optionally alternate the least-squares optimization of layer values with motion re-estimation.

FIG. **5** shows the operational and functional details of the present invention. For the case when the input composite images can be modeled as an additive mixture of the component layers (such a model applies when the light from one surface is reflected by another), a constrained least-square technique can be used to recover the layers from

known motions. Further, a complete technique that combines the layer extraction step together with an automatic multiple motion technique to recover the layers and their motions from the input images is preferably used.

In general, referring to FIG. **5**, along with FIG. **6**, first, an initial layer **510** of the original image sequence **200** of FIG. **2** is processed. From this processing, motion parameters **512** of the initial layer **510** are produced along with a difference sequence **514**. Preferably, the initial layer **510** is the desired layer that contains the dominant motion **600** of the image sequence **200**. Also, a stabilized image sequence **516**, with respect to the initial layer, along with a min composite **518** can be optionally produced. The min composite **518** can serve as an initial guess for the constrained least square calculation of FIG. **7**. The dominant motion estimation **600** for the sequence can be computed using image alignment against the current min-composite **518**. The difference image calculation is computed between the stabilized images and the min-composite **518**.

Next, the difference sequence **514** is used to process a secondary layer **520** of the original image sequence **200** of FIG. **2**. Referring to FIG. **4** along with FIG. **7**, with respect to the secondary layer **520**, motion parameters **522** of the secondary layer are produced. The secondary layer contains the non-dominant motion **700** of the image sequence **200**. Also, a stabilized image sequence **524** along with a max composite **526** can optionally be produced. The max composite **526** can serve as an initial guess for the constrained least square calculation of FIG. **8**. The non-dominant motion **700** can be computed by aligning the difference image calculation with the max-composite **526** of the images. Initial layer estimates of the dominant and non-dominant motion estimates **600**, **700** are then used to improve the motion estimates using motion re-estimation.

A constrained least squares technique **530** can be then used to recover the component layers **532**, **534**. Referring to FIG. **4** along with FIG. **8**, namely, the constrained least squares technique **530** can receive as input the original image sequence **200**, the motion parameters of the initial and secondary layers **510**, **520** and the min and max composites **518**, **526**. The constrained least-square calculation **530** solves for the layers by first performing a preconditioned conjugate gradient (PCG) **800** and then it enforces a positivity constraint by using a quadratic programming module **814**. In other words, the preconditioned conjugate gradient **800** with unconstrained least-squares can be computed for producing initial value estimates **810**, **812** and the positivity constraints can be used to solve a quadratic with the quadratic programming module **814** that is related to the layer extraction to extract the initial and secondary layers **816**, **818**. Alternatively, instead of running PCG, the MIN/MAX composites can be used as initial guess to the quadratic programming. Finally, the entire process can be repeated for a couple of times to refine the result.

IV. CONCLUSION

In summary, the present invention extracts a set of component layers from a collection of composite images. While the problem of recovering the multiple motions from such sequences has been extensively studied (at least when the motions are parametric), the problem of extracting the layer images in the presence of reflections and transparency has not been adequately treated until now.

The present invention is embodied in a system and method for recovering the layer images and their motions from the input sequence. For the case when the input composite images can be modeled as an additive mixture of the component layers (such a model applies when the light from one surface is reflected by another), a constrained least-square technique can be used to recover the layers from known motions. Further, a complete technique that combines the layer extraction step together with an automatic multiple motion technique to recover the layers and their motions from the input images has been described.

The foregoing description of the invention has been presented for the purposes of illustration and description. It is not intended to be exhaustive or to limit the invention to the precise form disclosed. Many modifications and variations are possible in light of the above teaching. It is intended that the scope of the invention be limited not by this detailed description, but rather by the claims appended hereto.

What is claimed is:

1. A method for performing layer extraction from multiple images containing reflections and transparencies, comprising:

computing a primary motion estimate, wherein computing the primary motion estimate includes computing a dominant motion for the sequence using image alignment against a current min-composite;

estimating a primary layer associated with the primary motion estimate, wherein estimating the primary layer includes computing a difference image calculation between stabilized images and the min-composite;

computing a secondary motion estimate, wherein computing the secondary motion estimate includes computing non-dominant motion by aligning the difference image calculation with a max-composite of the images;

estimating a secondary layer associated with the secondary motion estimate; and

iteratively refining lower and upper bounds on the primary and secondary layers to estimate the primary and secondary layers.

2. The method of claim **1**, further comprising improving the motion estimates using motion re-estimation.

3. The method of claim **1** further comprising stabilizing the images with respect to the primary layer.

4. The method of claim **3**, further comprising aligning the images against a current min-composite and computing a difference image calculation between the stabilized images and the min-composite to produce the initial layer estimate.

5. The method of claim **3**, wherein iteratively refining includes recovering the primary layer and the secondary layer of the images.

6. The method of claim **1**, wherein estimating the layers includes using constrained least squares to optimally recover the layer images.

7. The method of claim **6**, further comprising alternating the least-squares optimization of layer values with motion re-estimation.

8. The method of claim **7**, further comprising computing an unconstrained least-squares solution and using the result of the least squares computation as the initial value and solving the quadratic-programming problem with positivity constraints.

9. The method of claim **6** wherein using constrained least squares to optimally recover the layer images, comprises:

using known motion parameters to compute a preconditioned conjugate gradient without constraints to determine gradient parameters; and

estimating the components based on the gradient parameters.

10. The method of claim 9, further comprising using positivity constraints to solve a quadratic related to the extracted images.

11. The method of claim 10, wherein the motion parameters are determined by computing a dominant motion for the sequence using image alignment against a current min-composite; computing a difference image calculation between stabilized images and the min-composite;

and computing non-dominant motion by aligning the difference image calculation with a max-composite of the images.

12. A computer-readable medium having computer-executable instructions for performing the method recited in claim 9.

13. The method of claim 1, wherein the multiple images form a video sequence containing reflections and transparencies.

14. The method of claim 1, further comprising using initial layer estimates of the dominant and non-dominant motion estimates and improving the motion estimates using motion re-estimation and computing unconstrained least-squares as an initial value and using positivity constraints to solve a quadratic related to the layer extraction.

15. A computer-readable medium having computer-executable instructions for performing the method recited in claim 1.

16. The method of claim 1 wherein the upper and lower bounds are refined by the process actions of:

aligning the images against a current minimum composite;

computing a difference image calculation between the images and the minimum composite; and

aligning the difference image calculation with a maximum composite of the images.

17. The method of claim 16, further comprising continually performing the method a predefined amount to iteratively refine lower and upper bound parameters of the images.

18. The method of claim 16, computing unconstrained least-squares as an initial value and using positivity constraints to solve a quadratic related to the extracted images.

19. A computer-readable medium having computer-executable instructions for performing the method recited in claim 16.

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